Fusion of hyperspectral and panchromatic images using multiresolution analysis and nonlinear PCA band reduction

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FUSION OF HYPERSPECTRAL AND PANCHROMATIC IMAGES USING MULTIRESOLUTION ANALYSIS AND NONLINEAR PCA BAND REDUCTION

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ABSTRACT

This paper presents a novel method for the enhancement of spatial quality of Hyperspectral (HS) images while making use of a high resolution panchromatic (PAN) image. Due to the high number of bands the application of a pansharpening technique to HS images may result in an increase of the computational load and complexity. Thus a dimensionality reduction preprocess, compressing the original number of measurements into a lower dimensional space, becomes mandatory. To solve this problem we propose a pansharpening technique combining both dimensionality reduction and fusion, exploited by non-linear Principal Component Analysis and Indusion respectively, to enhance the spatial resolution of a hyperspectral image.

Index Terms— Neural Network, NLPCA, Hyperspectral image, Pansharpening, Image fusion.

1. INTRODUCTION

Generally, for satellite images the highest spatial resolution is captured by the PAN image; however, it has no spectral diversity. Unlike PAN images, Multispectral and in particular Hyperspectral satellite images have good spectral resolution. Compared to multispectral (MS) images, HS images have a better spectral resolution. This results in a very high number of bands, but, on the other hand, they have the drawback of having a low spatial resolution. For better utilization and interpretation, hyperspectral images having both high spectral and spatial resolution are desired. This can be achieved by making use of a high spatial resolution PAN image in the context of pansharpening.

Pansharpening, or image fusion, is the process of improving the spatial quality of a low spatial resolution image (HS or MS) by fusing it with a high resolution PAN image. One of the main challenges in image fusion is to improve the spatial resolution, i.e. spatial details, while preserving the original spectral information. This requires addition of spatial details to each band of the image. Due to the high number of bands the pansharpening of HS images results in increased computational load and complexity. Thus a dimensionality reduction preprocess, compressing the original number of measurements into a lower dimensional space, becomes mandatory. In this paper we propose a new approach to enhance the spatial resolution of a hyperspectral image combining both nonlinear Principal Component Analysis and Indusion for dimensionality reduction and fusion respectively.

2. DIMENSIONALITY REDUCTION

The main difficulty in processing HS images is related to the number of bands. Applying a pansharpening technique to each band of the HS image, can lead to an enormous increase of the computational time of the entire process. Hence, while processing a hyperspectral image, it is generally desirable to reduce the number of bands to avoid loss of relevant information of the original dataset. Moreover, it is also important that the reduction method allows a reconstruction of the original spectral information content. The most common techniques to reduce the number of bands are the Minimum Noise Fraction (MNF), Principal Component Analysis (PCA) and also Independent Component Analysis (ICA)[1] [2]. For all of them, the dimensionality reduction is performed by discarding the components with the lowest information content. Also, for both techniques, the components obtained are linearly uncorrelated but the physical representation of the image may be lost. Moreover, being linear methods, PCA and MNF assume that the observed data set is composed of linear combinations of certain basis. Other approaches are based upon the characteristic of hyperspectral images of having adjacent bands spectrally high correlated [3][4].

In the proposed approach, dimensionality reduction is achieved by using nonlinear principal component analysis (NLPCA), commonly referred to as nonlinear generalization of standard principal component analysis. The nonlinear principal components (NLPC) are obtained with an autoassociative neural network (AANN), overcoming the limitations of linear principal component analysis. The AANN are NN of a conventional

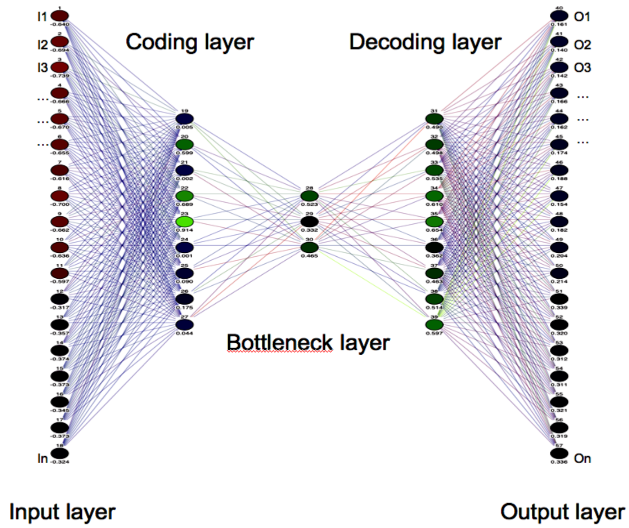


Fig. 1. *Auto-associative neural networks used for feature reduction. The outputs at the nodes of the bottle-neck layer are the nonlinear principal components.*

type, i.e. featuring feedforward connections and sigmoidal nodal transfer functions, trained by backpropagation or similar algorithms. The particular network architecture used employs three hidden layers, including an internal bottleneck layer of smaller dimension than either input or output (Fig. 1) . The network is trained to perform identity mapping, where the input is approximated at the output layer. Since there are fewer units in the bottleneck layer than the output, the bottleneck nodes must represent or encode the information obtained from the inputs for the subsequent layers to reconstruct the input. The concept of using a neural network with a bottleneck to concentrate information has been originally introduced in [5] and it has been effectively applied in the dimensionality reduction of huge datasets such as HS images [6]. Compared to linear reduction techniques, NLPCA has many advantages. First of all, while PCA and MNF can detect and discard linear correlations among spectral bands, NLPCA detects both linear and nonlinear correlations. Moreover, in NLPCA the information content is equally distributed among the components, allowing NLPCA to be significantly more effective than PCA or MNF in the inverse operation of reconstruction of the original spectral information [6].

3. IMAGE FUSION

The fusion of HS and PAN images is a useful technique for enhancing the spatial quality of low-resolution images. Generally, the fusion process can be subdivided into two steps. In the first step the low resolution image is scaled up to the same size as the PAN image. Next, fusion is achieved by adding high-fequency content of the PAN to HS image. Literature on pansharpening methods is rich with diversity, encompassing methods based upon the use of discrete wavelet transform (DWT), PCA (Principal Component Analysis) transform, and IHS (Intensity-Hue-Saturation) transform. The latter two methods, that fall in the category of component substitution methods, result in fused images having high spatial quality, but suffering from spectral distortions [7]. The images fused using DWT are not as sharp as component substitution methods but they are spectrally consistent. In this paper we propose to use INDUSION for pansharpening. Introduced in [8], INDUSION is a pansharpening technique derived from the Induction scaling technique. The Induction technique, considers enlargement as the inverse problem of reduction. This yields the condition that an enlarged image should, when reduced, give the initial image back. This condition is called the *reduction constraint*. For a given image and a reduction filter, there is a set of enlarged images that verifies the *reduction constraint*. This set of images is called the induced set. Induction, initially developed for image magnification [9], simply consists in projecting an upscaled image, not adhering to the reduction constraint, onto the induced set so as to obtain an induced image that belongs to the induced set. Applied to remote sensing, the concept of image fusion consists in the extraction of the high-frequency information from the PAN image and in adding it to the upscaled low-resolution image. The idea of Indusion is to replace the unconstrained upscaled image by the PAN image since we want the high-frequency information of the PAN image to be added to the upscaled NLPCA image obtained from the original HS dataset. In addition, more high frequency information can be generated by changing the parameters in the induction process such as the reduction kernel. In fig. 2 the complete scheme of the proposed method is depicted. First, each dataset is reduced by mean of NLPCA. Then the reduced set, composed by non-linear principal components, is fused with the PAN image to enhance its spatial resolution. Finally the inverse NLPCA is applied to the fused image. This procedure permits to enlarge HS data preserving the original spectral information.

4. RESULTS

In this paper, the proposed method was applied to a CHRIS-Proba dataset and a QuickBird Panchromatic image acquired in different period of 2006 over the Tor Vergata area, south-east of Rome, Italy. The PROBA (PRoject for On Board Autonomy) spacecraft is a mini-satellite operated by the European Space Agency. The main payload of PROBA is the CHRIS (Compact High Resolution Imaging Spectrometer) sensor which can acquire up to 63 spectral bands (400 nm - 1050 nm) with nominal spatial resolutions of 17 m or 34 m at nadir. The CHRIS sensor allows 5 different acquisition modes (aerosol, land cover, vegetation and coastal zones), according to the number and location of spectral bands, the spatial resolution and the width of the swath. Thus, the CHRIS-PROBA system allows to acquire hyperspectral im-

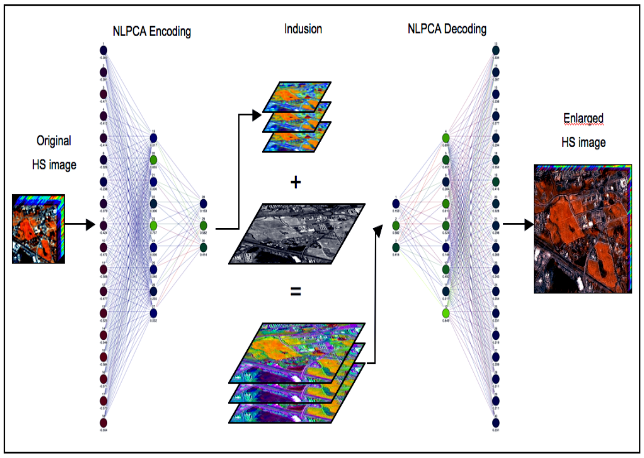
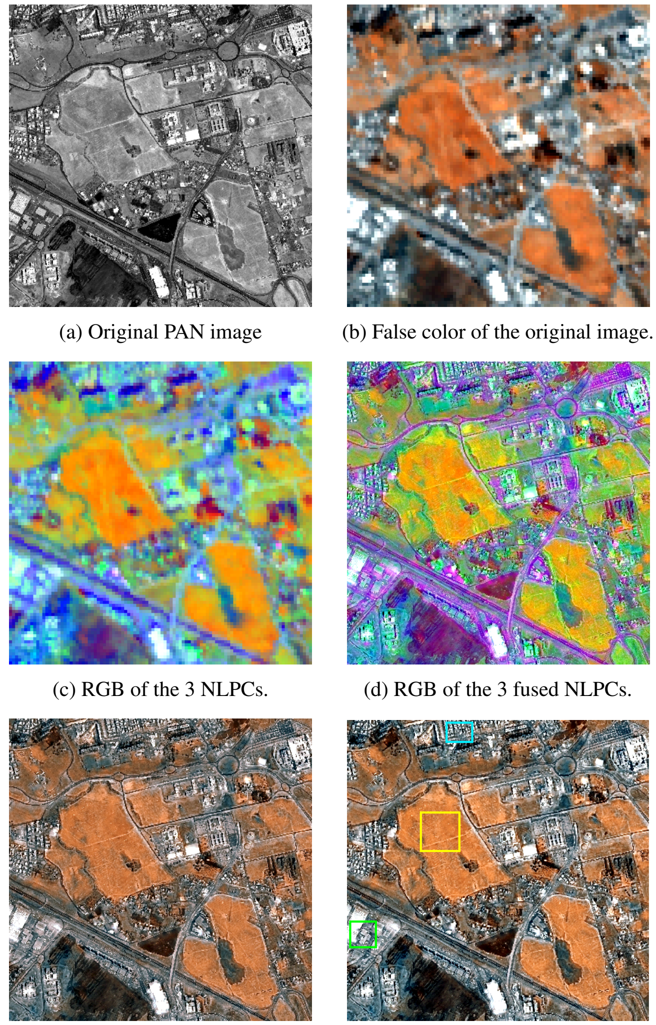


Fig. 2. *Complete scheme of the proposed technique. The three NLPCs are firstly extracted from the original CHRIS-Proba image and then fused with the PAN according to the Indusion process. The fused NLPCs are then transformed back into 18 enlarged CHRIS-Proba bands.*

ages of the same scene with five different view angles during a single overpass: +55°, +36°, 0°, -36° and -55°. To test the proposed approach a 0° image, acquired in Land-Cover mode (18 bands), was used. The CHRIS image was atmospherically corrected, projection and accurately co-registered to the PAN image. A subset of 216x216 pixels for the CHRIS image and 864x864 for the PAN image was then selected. To obtain an enlargement ratio of 4, the CHRIS image and the PAN image have been degraded to the spatial resolutions of 20 and 5 meters respectively.

The dimensionality reduction phase was performed by extracting the nonlinear principal components. To detect the best topology configuration for the AANN, a grid-search approach was followed. The best solution was found with 18 inputs/output, 9 nodes both in the outer hidden layers and 3 nodes in the bottleneck. The mean square error (MSE) obtained after 500 training cycles was 0.003. The three NLPCs are then enlarged with a ratio of 4, following the Indusion approach, fusing them with the PAN image. Fig. 3(a) and (e) report respectively a false color representation of the original image and of the fused image. Fig. 3(c) and (d) show respectively a RGB composite obtained combining the three NLPC from the original CHRIS-Proba image and the result of the Indusion process applied to the three NLPCs.

For the quantitative quality assessment it is generally recommended to make use of the synthesis property as proposed by Wald in [10]. This means that both the HS and Pan images are degraded to a lower resolution and then Pansharpening is performed. The resultant pansharpened image is at the same resolution as the starting reference and hence statistical analysis can be made between the reference and pansharpened images. Since we already have the reference image at the



(a) Original PAN image

(b) False color of the original image.

(c) RGB of the 3 NLPCs.

(d) RGB of the 3 fused NLPCs.

(e) Resulting fused image.

(f) Quality assessment areas.

Fig. 3. PAN image (a), original CHRIS image (b) and result of the different steps of the proposed procedure.

same resolution of the fused image we can perform UIQI, ERGAS and Spectral Angle Mapper (SAM) calculations between the pansharpened and reference image [10][11]. The ideal values for ERGAS, SAM and UIQI indices are 0, 0 and 1, respectively. However, if we reduce our images to a lower resolution, there will be no significant information left in the images and hence the pansharpened images would not be at a good resolution. A solution to this issue is to use as reference image the original non-degraded image while downscaling the fused image, using Bicubic convolution filter, matching the original spatial resolution. To better evaluate the quality of the proposed method, in table 1 are reported the quality indexes derived not only for the entire image but also for the different areas in the image representing three main types in the scene (industrial buildings, dense residential areas and pastures). In addition, the quality indexes have been computed on the output of the AANN and INDUSION separately, this to evaluate their capability in preserving the spectral integrity of the original image. In the first evaluation the output of the complete AANN has been compared with the original image, while in the latter the output of the Indusion process has been compared with the three original nonlinear principal components. From a qualitative visual analysis, the fused images obtained from the proposed approach appear to be very sharp and spectrally consistent related to the original images. Also the quantitative analysis, carried out evaluating the quality indexes, shows very good values for the pansharpened images. It is important to notice that, despite of an overall good quality, the indexes values for the Pasture and Industrial areas are very good, while the worst result was obtained on the dense urban fabric. This effect can explained because of the different acquisition dates and geometry of the PAN and CHRIS-Proba images. Another element of distortion came from the differences of the burned areas in the lower-left and lower-center parts of the image.

	UIQI	ERGAS	SAM
Reference	1	0	0
NLPCA	0.9945	0.7953	0.8317
INDUSION	0.9627	1.6798	2.3751
Complete image	0.9229	2.6797	2.7413
Pasture	0.9373	2.2180	2.1511
Industrial	0.9313	2.2978	2.3871
Dense Urban fabric	0.8616	4.1971	3.9812

Table 1. UIQI, ERGAS and SAM quality indexes.

5. CONCLUSION

In this paper, we have presented a novel approach for pansharpening of hyperspectral images preserving the spectral quality of the original image. The proposed method introduces NLPCA as dimensionality reduction technique applied to hyperspectral images. The UIQI and ERGAS quality indexes demonstrate quantitatively a good performance of the proposed method on CHRIS-Proba and a QuickBird PAN image. A visual analysis and a quantitative evaluation assess the performance of the proposed algorithm. Visually, Indusion produced sharp and least spectrally distorted images while NLPCA reduced the original dataset dimensionality avoiding further spectral distortions. Moreover it has to be noted that being the two used images real datasets, acquired by different instruments with different acquisition geometry and dates, it was not possible to avoid the presence of some differences between the two datasets.

Future studies will investigate the assessment of the proposed method applied to datasets with a higher number of bands. Moreover comparisons with other techniques will also be evaluated.

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